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Denoising of A Mixed Noise Color Image Through Special Filter

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Abstract

Image denoising is the manipulation of the image data to produce a visually high quality image. At present there are a variety of methods to remove noise from digital images. There are different types of filters like mean filter, median filter, bilateral filter, wiener filter etc. to remove a single type of noise such as salt and pepper noise, speckle noise, Gaussian noise etc. But if the image is corrupted by mixed noise then these filters do not remove the noise exactly. Here a white flower image has been taken for denoising purpose. The white flower image is corrupted by mixed noise at zero mean and different variances to produce different noisy images at zero mean and respective variances. Noisy image is denoised by discrete wavelet transform (DWT) denoising technique using 'Haar' wavelet and different filters like median filter, wiener filter and bilateral filter one-by-one to produce noise free image as much as possible. Different parameters like MSE (mean square error), PSNR (peak signal to noise ratio), RMSE (root mean square error), SNR (signal to noise ratio) and SSIM (structural similarity index) estimate the performance of all filters. Special filter is designed with the help of these performance estimations so that a better filter for mixed noise image denoising purpose can be implemented. All mixed noisy images are denoised by the special filters and their performance parameters are estimated. The special filter is a combination of various filters and denoising techniques to remove of mixed noise from a digital image. The comparisons between noisy and denoised images of the special filter and other filters are presented in the form of graphs and tables.

***Keywords**: salt-and-pepper noise; gaussian noise; speckle noise; wavelet denoising; median filter; bilateral filter; wiener filter; psnr; snr; rmse; mse; ssim*

1. Introduction

A digital image is defined as a two dimensional discrete function f (i; j), where i and j are spatial co-ordinates of the image f. (i; j) denotes a location of the image. The value of i and j vary depending on the dimension of the image, however, the value of f (i; j) is limited between 0 - 255 for gray-scale images. The value of f (i; j) for any given i and j is called the intensity of the image at location (i; j). The intensity is also known as brightness or pixel value of the image.

There are a number of mechanical and electronic interference introduced during the image acquisition process. Such interferences generate some unexpected or random brightness information known as noise. Having a good knowledge about the noise present in the image is important in selecting a suitable denoising algorithm [5]. The denoising methods include Gaussian filtering and Wiener filtering etc. However, these methods lose fine details of the image which leads to blur in the image. [6]. Impulsive noises are commonly found in the sensor or transmission channel during the acquisition and transfer procedure. Salt-and-pepper noise is a typical kind of impulsive noise. It is well known

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that linear filtering techniques fail when the noise is non-additive and are not effective in removing impulse noise. The nonlinear filter algorithms are often adopted for the salt-and-pepper noise removal. The widely used nonlinear digital filter is median filter. Median filter is known for their capability to remove impulse noise. The main drawback of a standard median filter (SMF) is that it is effective only for low noise densities. At high noise densities, SMFs often exhibit blurring for large window sizes and insufficient noise suppression for small window sizes. DWT denoising technique reduces speckle noise effectively but in case of other noise it does not provide satisfactory results. Wiener and bilateral denoise better in case of gaussian noise image. Bilateral filter denoises speckle noise better than wiener filter.

Special filter consists the properties two or more filters. Special filter can remove the additive, multiplicative as well as mixed noise effectively and can produce denoised image of higher quality in comparison to single filtering technique.

Noise is a random variation of image Intensity and visible as grains in the image. It may arise in the image as effects of basic physics-like photon nature of light or thermal energy of heat inside the image sensors [17].

Here we are discussing about three types of noise and their effect on the image signal.

1. Gaussian noise
2. Speckle noise
3. Salt-and-pepper noise

This noise model is additive in nature. Additive white Gaussian noise (AWGN) can be caused by poor quality image acquisition, noisy environment or internal noise in communication channels. Gaussian noise is statistical noise having a probability density function (PDF) equal to that of the normal distribution, which is also known as the Gaussian distribution [9]. Gaussian noise is uniformly distributed over the signal. It means that each pixel in the noisy image is the sum of the true pixel value and a random value of Gaussian distributed noise [10]. It is given by:

$$F(g) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(g-m)^2}{2\sigma^2}}$$

Where g = gray level, m = mean or average of the function, σ2 = variance of the noise.

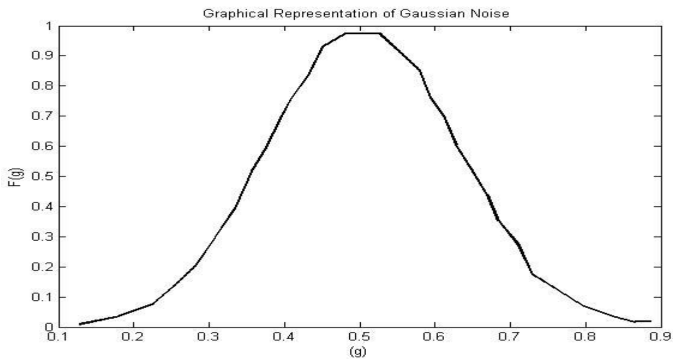


Figure 1. Graphical Representation of Gaussian Noise [2]

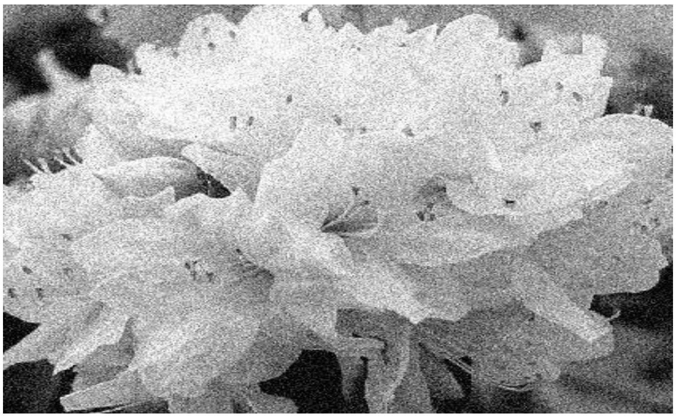


Figure 2. Gaussian Noise at 0 Mean and 0.02 Variance

Speckle noise is an inherent nature of ultrasound images, which may have negative effect on image interpretation and diagnostic tasks. Speckle noise significantly degrades the image quality and complicates diagnostic decisions for discriminating fine details in ultrasound images [18]. Speckle noise is a kind of multiplicative noise. Speckle-noise is a granular noise degrades the quality of the active radar, synthetic aperture radar (SAR), and medical ultrasound images. Speckle noise occurs in conventional radar due to random fluctuations in the return signal from an object [12].Speckle noise follows a gamma distribution and is given as:

$$F(g) = \frac{g^{\alpha-1}}{(\alpha-1)!a^{\alpha}} e^{-\frac{g}{a}} \quad [10]$$

Where a = variance & g = gray level

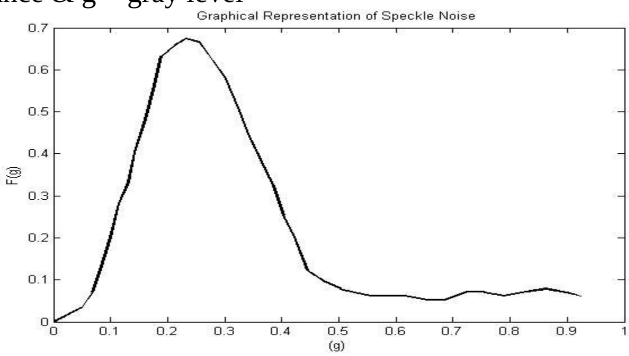


Figure 3. Graphical Representation of Speckle Noise [2]

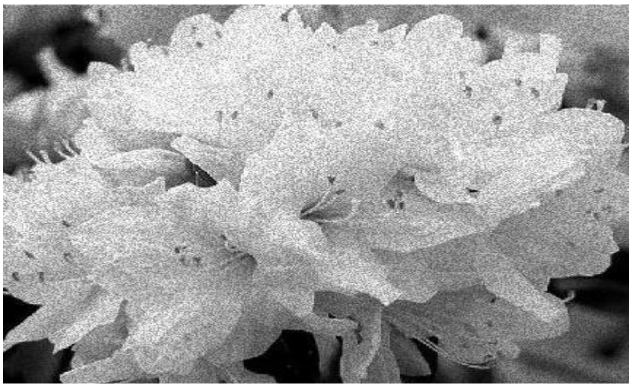


Figure 3. Speckle Noise at 0 Mean and 0.02 Variance

Salt-and-pepper noise is also called impulsive noise or spike noise [9]. Salt-and-pepper noised image has dark pixels in bright area and bright pixels in dark area of the image. It has only two possible values, a high value and a low value. This noise occurs during analog-to-digital converter errors, bit errors in transmission [12]. Salt-and-pepper noise can severely damage the information or data embedded in the original image. One of the simplest ways to remove salt-and-pepper noise is by windowing the noisy image with a conventional median filter [15].The probability density function.

(PDF) for impulsive noise is given by:

$$F(g) = \begin{cases} P_a & g = a \\ P_b & g = b \\ 0 & otherwise \end{cases}$$

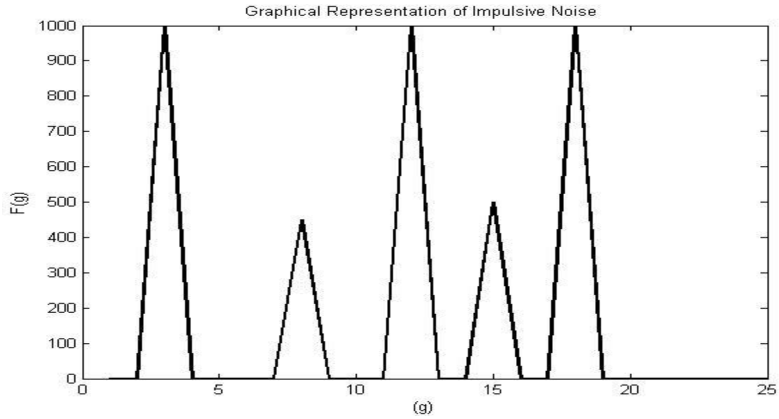


Figure 4. Graphical Representation of Impulsive Noise [2]

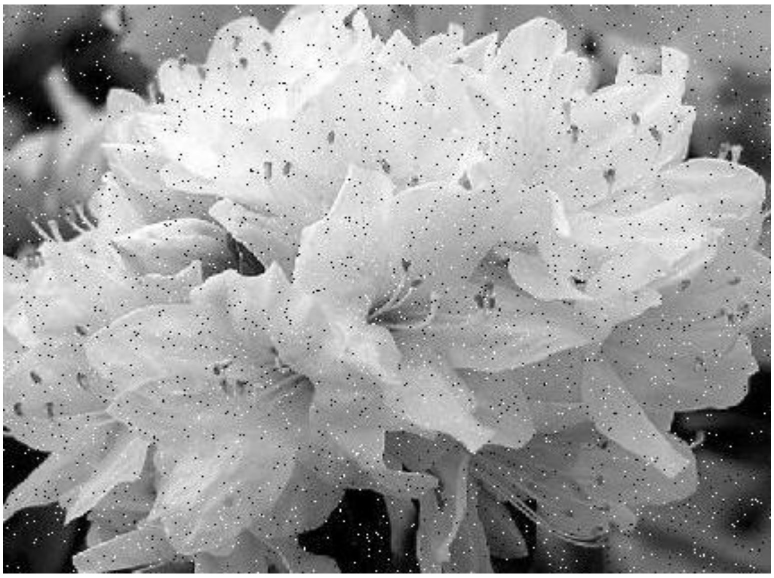


Figure 5. Salt & Pepper Noise at 0 Mean and 0.02 Variance

2. Mixed Noise

Mixed noise is a mixture of two or more types of noises at same or different means and variances. Here, mixed noise is generated by adding gaussian noise with speckle noise and combination of both noises is added with salt & pepper noise at zero mean and different variances.

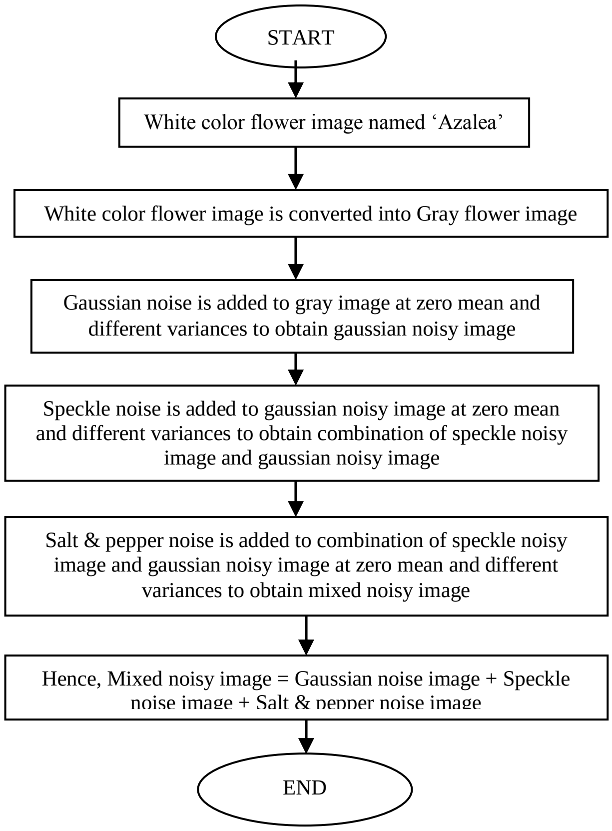


Figure 6. Flowchart of Mixed Noise

3. Discrete Wavelet Transform

Simple de-noising algorithms that use the wavelet transform consist of three steps.

1. Calculate the wavelet transform of the noisy signal.

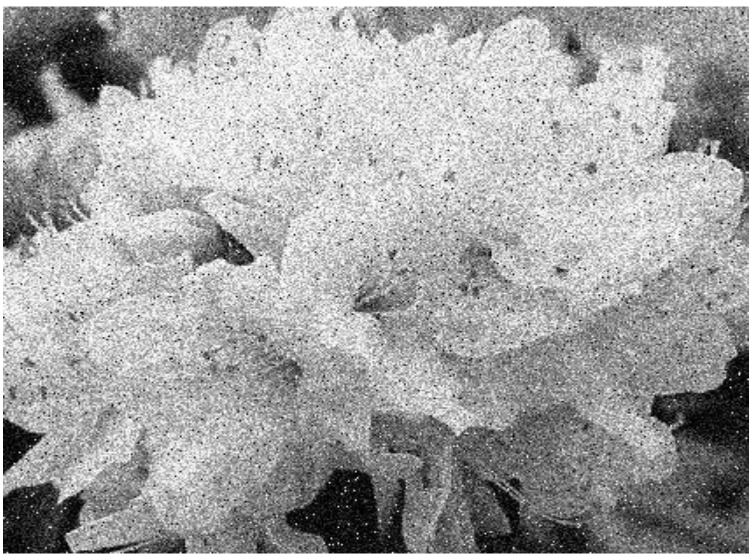


Figure 7. Mixed Noise at Zero Mean and 0.02 Variance

2. Modify the noisy wavelet coefficients according to rule. Soft thresholding and hard thresholding are most well known rules.
3. Compute the inverse transform using the modified coefficients.

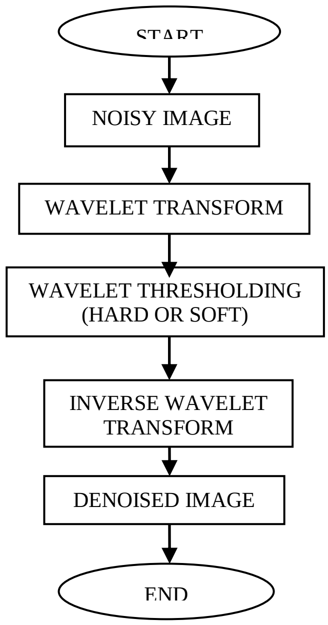


Figure 8. Flowchart of DWT

Discrete Wavelet Transform has attracted more and more interest in image de-noising. The signal S is passed through two complementary filters and emerges as two signals, approximation and Details. This is called decomposition or analysis. The components can be assembled back into the original signal without loss of information. This process is called reconstruction or synthesis. The mathematical manipulation, which implies analysis and synthesis, is called discrete wavelet transform and inverse discrete wavelet transform. An image can be decomposed into a sequence of different spatial resolution images using DWT. In case of a 2D image, an N level decomposition can be performed resulting in 3N+1 different frequency bands namely, LL, LH, HL and HH as shown in figure. These are also known by other names, the sub-bands may be respectively called a1 or the first average image, h1 called horizontal fluctuation, v1 called vertical fluctuation and d1 called the first diagonal fluctuation. The sub-image a1 is formed by computing the trends along rows of the image followed by computing trends along its columns. In the same manner, fluctuations are also created by computing trends along rows followed by trends along columns. The next level of wavelet transform is applied to the low frequency sub band image LL only. The noise will nearly be averaged out in low frequency wavelet coefficients. Therefore, only the wavelet coefficients in the high frequency levels need to be thresholded. H is high frequency band while L is low frequency band and 1, 2…are decomposition levels.

<table>
<tr><td>LL^2</td><td>LH^2</td><td rowspan="2">LH^1</td></tr>
<tr><td>HL^2</td><td>HH^2</td></tr>
<tr><td colspan="2">HL^1</td><td>HH^1</td></tr>
</table>

Figure 9. 2D-DWT with 2-Level Decomposition

4. Median Filter

Median filtering has a good edge preserving ability, and does not introduce new pixel values to the processed image [1]. The Median filter is a non-linear smoothing technique that reduces the blurring of edges; here the idea is to replace the current point in the image by the median of the brightness in its neighborhood. The median of the brightness in the neighborhood is not affected by individual noise spikes. The median filter eliminates impulse noise efficiently. Since median filtering does not blur edges much, it can be applied iteratively. One of the major problems with the median filter is that it is relatively expensive and is hard to compute. It is essential to sort all the values in the neighborhood into numerical in order to find out the median value which is relatively slow [5].Median filter is based on the following steps: [6]

- It checks for pixels that are noisy in the image.
- For each such pixel P, a window of size 5×5 around the pixel P is taken.
- Find the absolute differences between the pixel P and the surrounding pixels.
- The arithmetic mean (AM) of the differences for a given pixel p is computed.
- The AM is then compared with the ―threshold to detect whether the pixel p is informative or corruptive.

a) If AM is greater than or equal to the threshold the pixel is considered noisy.

b) Otherwise the pixel is considered as information.

The filter fails to perform well at higher noise densities. When noise density is high it is highly unlikely that there might be more informative pixels than corruptive pixels.

5. Weiner Filter

Wiener filters are a class of optimum linear filters which involve linear estimation of a desired signal sequence from another related sequence. It is not an adaptive filter. The wiener filter’s main purpose is to reduce the amount of noise present in a image by comparison with an estimation of the desired noiseless image. The Wiener filter may also be used for smoothing. This filter is the mean squares error-optimal stationary linear filter for images degraded by additive noise and blurring. It is usually applied in the frequency domain (by taking the Fourier transform), due to linear motion or unfocussed optics Wiener filter is the most important technique for removal of blur in images. Each pixel in a digital representation of the photograph should represent the intensity of a single stationary point in front of the camera. Unfortunately, if the shutter speed is too slow and the camera is in motion, a given pixel will be an amalgam of intensities from points along the line of the camera's motion.

The goal of the Wiener filter is to filter out noise that has corrupted a signal. It is based on a statistical approach. Typical filters are designed for a desired frequency response. The Wiener filter approaches filtering from a different angle. One is assumed to have knowledge of the spectral properties of the original signal and the noise, and one seeks the LTI filter whose output would come as close to the original signal as possible

Wiener filters are characterized by the following:

a. Assumption: signal and (additive) noise are stationary linear random processes with known spectral characteristics.

b. Requirement: the filter must be physically realizable, *i.e.*, causal (this requirement can be dropped, resulting in a non-causal solution)

c. Performance criteria: minimum mean-square error [13]

Weiner filtration gives an estimate of the original uncorrupted image with minimal mean square error; the optimal estimate is in general a non-linear function of the corrupted image.

The function can be written by,

$$f(u,v) = \left[\frac{H(u,v)^*}{H(u,v)^2 + \left[\frac{Sn(u,v)}{Sf(u,v)}\right]}\right] G(u,v) \quad [11]$$

where $H(u,v)$is the degradation function & $H(u,v)^*$ is its conjugate complex and $G(u,v)$ is the degraded image. Functions $Sf(u,v)$ and $Sn(u,v)$are power spectra of the original image and the noise [5].

6. Bilateral Filtering

The bilateral filtering is an edge-preserving smoothing technique which effectively blurs the image but maintains the sharpness of edges [14]. The bilateral filtering was introduced by Tomasi and Manduchi. It is achieved by the combinations of the two Gaussian filters. One filter works in spatial domain and the second filter works in intensity domain. It is a non-linear filter where the output is a weighted average of the input. The output of the bilateral filter for a pixel s is defined as follows: [7]

$$J(s) = \frac{1}{K(s)} \sum_{p\epsilon\, \emptyset} (p-s)(I_p - I_s) I_p$$

Where k(s) is a normalization term:

$$K(s) = \sum_{p\epsilon\emptyset} f(p-s) g(I_p - I_s)$$

Where f uses a Gaussian in the spatial domain which is represents the domain filter and g uses a Gaussian in the intensity domain which represents the range filter. Domain filtering can be expressed mathematically as:

$$J(s) = \frac{1}{K_d(s)} \sum_{p\epsilon\emptyset} f(p-s) I_p$$

Where $f(p-s) = exp^{-\frac{\|p-s\|^2}{2\sigma d^2}}$f (p-s) measures the spatial closeness between the neighborhood center s and a nearby point p and:

$$K_d(s) = \sum_{p\epsilon\emptyset} f(p-s)$$

Range filtering is defined as follows:

$$J(s) = \frac{1}{K_r(s)} \sum_{p \epsilon \emptyset} g(I_p - I_s) I_p$$

Where $g\left(I_p - I_s\right) = exp \frac{\left\|I_p - I_s\right\|^2}{2\sigma d^2}$

$g\left(I_p - I_s\right)$ measures the photometric similarity between the center pixel s and its nearby point p. The normalized constant in this case is:

$K_r(s) = \sum_{p \epsilon \emptyset} g(I_p - I_s).$

7. Special Filter

Special filter is a combination of three filters median filter, wiener filter and bilateral filter. The performance of the Median filter after de-noising for all Salt & Pepper noise is better than mean filter a Wiener filter. The performance of the Wiener Filter after de-noising for all Speckle and Gaussian noise is better than Median filter. Wavelet denoising technique produces blur image. Wavelet denoising technique loses details of the image and produce smooth image sharpness of image is lost. So, there is a need of such filter that removes mixed noise and produces a good quality image with loss of as small as possible value of information of the image during denoising process.

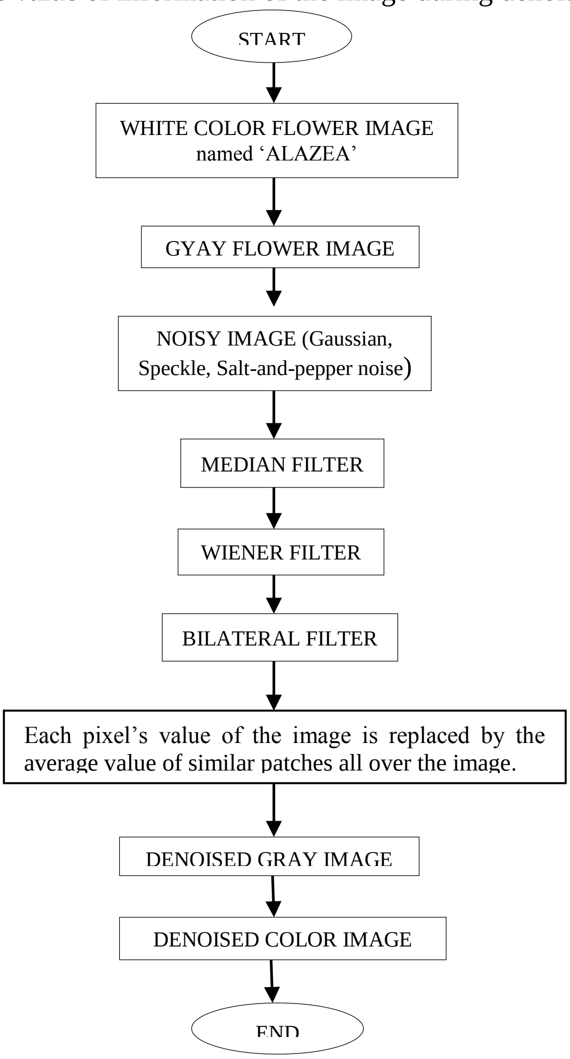


Figure 10. Flow Chart of Special Filter

Steps for designing Special filter model:

- A color image is taken for experiment purpose.
- The color image is converted into gray image.
- Mixed noise image is obtained by adding three different nois0es (Gaussian, speckle, salt and pepper noises) at zero mean and different variances.
- Mixed noise is filtered first by median filter.
- Median filtered image is filtered by wiener filter.
- Wiener filtered image is filtered by bilateral filter.
- Each pixel's value of bilateral filtered image is replaced by the average value of similar patches all over the image.
- Denoised image is a gray image so it is converted into color RGB image. This is the final denoised image.

8. Performance Parameters

For comparing original white color image with noisy and denoised images, we calculate following parameters:

A. Mean Square Error (MSE):

The MSE is the cumulative square error between the synthesized image and the original image defined by:

$$\mathrm{MSE} = \sum_0^{m-1} \sum_0^{n-1} \left| |f(i,j) - g(i,j)| \right|^2 \quad [8]$$

Where, f is the original image and g is the synthesized image. MSE should be as low as possible.

B. Peak signal to Noise ratio (PSNR):

PSNR is the ratio between maximum possible power of a signal and the power of distorting noise which affects the quality of the original signal [12]. It is defined by:

$$\mathrm{PSNR} = \frac{20 \log_{10}(\mathrm{MAX_F})}{\sqrt{\mathrm{MSE}}} \ [2].$$

Where $\mathrm{MAX_F}$ is the maximum signal value that exists in our original image. PSNR should be as high as possible.

C. Root mean square error (RMSE):

It measures of the differences between value predicted by a model or an estimator and the values actually observed. It is the square root of mean square error. RMSE should be as low as Possible.

$$\mathrm{RMSE} = \sqrt{\mathrm{MSE}}$$

D. Similarity Index (SSIM):

It is a method for measuring the similarity between two images [16]. The SSIM measure the image quality based on an initial distortion-free image as reference.

$$\mathrm{SSIM} = \frac{(2\mu_X\mu_Y + C_1)(2\sigma_{XY}C_2)}{(\mu_X^2 + \mu_Y^2 + C_1)(\sigma_X^2 + \sigma_Y^2 + C_2)}$$

μ_X the average of x;

μ_Y the average of y;

σ_X^2 the variance of x;

σ_Y^2 the variance of y;

$\sigma_{XY}$the covariance of x and y;

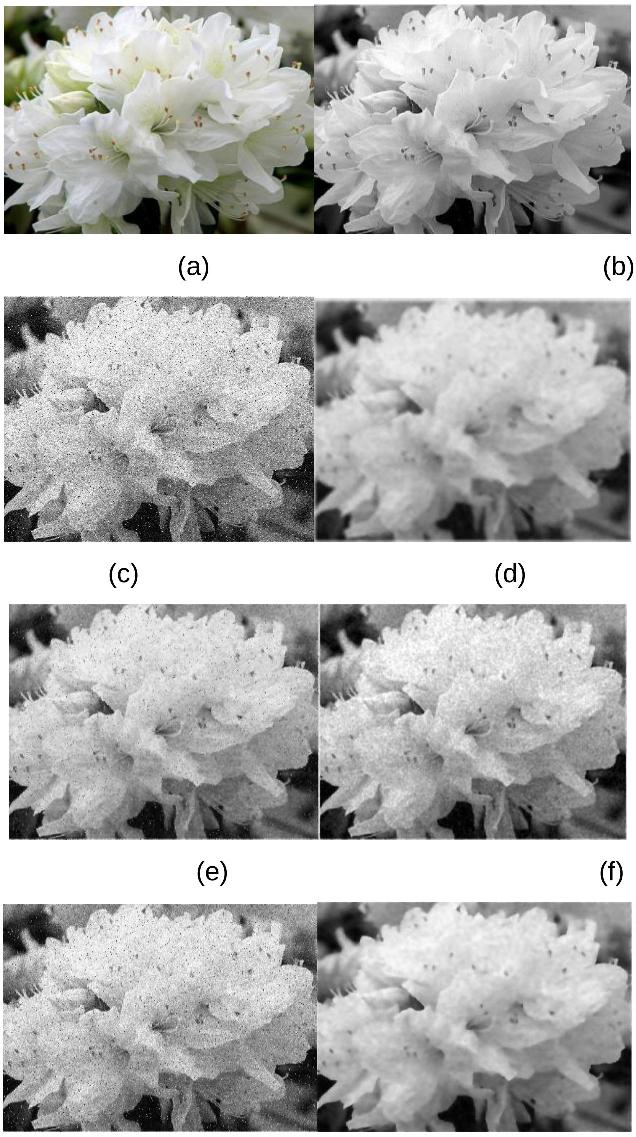
C_1= $(k_1L)^2$ and C_2 = $(k_2L)^2$ are two variables to stabilize the division with weak denominator. L the dynamic range of the pixel-values $k_1 = 0.01$ and $k_2 = 0.03$ by default. The resultant SSIM index is a decimal value between -1 and 1, and value 1 is only reachable in the case of two identical sets of data.

E. Signal to noise ratio (SNR):

Signal-to-noise ratio is defined as the power ratio between a signal (meaningful information) and the noise (unwanted signal) It should be as low as possible:

$$SNR = \frac{P_{SIGNAL}}{P_{NOISE}}[4]$$

9. Result



(a) (b)

(c) (d)

(e) (f)

(g) (h)

(i)

Figure 10. (a) Original White color flower (b) Gray flower Image (c) Image obtained after adding all three noises (d) Image obtained after denoising by wavelet technique (e) Image obtained after filtering by wiener filter (f) Image obtained after filtering by median filter (g) Image obtained after filtering by bilateral filter (h) Image obtained after filtering by Special filter (i) Image obtained after converting gray Special filtered into a color image.

Table 1. Mixed Noise at Zero Mean and Different Variances and Mixed Noise Performance Parameters

Noise variance	Mixed noise performance parameters				
	PSNR	*SSIM*	*SNR*	*MSE*	*RMSE*
0.001	20.71	0.23	18.77	7.31e+05	8.55e+02
0.002	20.29	0.22	18.35	7.52e+05	8.67e+02
0.003	19.97	0.21	18.03	7.69e+05	8.77e+02
0.004	19.62	0.20	17.68	7.89e+05	8.88e+02
0.005	19.33	0.20	17.39	8.03e+05	8.98e+02
0.006	19.08	0.19	17.14	8.25e+05	9.07e+02
0.007	18.79	0.18	16.85	8.43e+05	9.18e+02
0.008	18.58	0.18	16.64	8.59e+05	9.26e+02
0.009	18.31	0.17	16.37	8.79e+05	9.37e+02
0.01	18.12	0.16	16.17	8.95e+05	9.46e+02
0.02	16.38	0.12	14.43	1.07e+06	1.03e+03

Table 2. Mixed noise at Zero Mean and Different Variances and PSNR of Different Filters and Special Filter

Noise Variance	PSNR				
	Wavelet denoising	*Median filter*	*Wiener filter*	*Bilateral filter*	*Special filter*
0.001	24.41	28.72	27.20	24.81	29.24
0.002	24.22	28.22	26.41	23.99	28.86
0.003	24.06	27.85	25.89	23.39	28.54
0.004	23.91	27.60	25.37	22.80	28.36
0.005	23.79	27.43	24.98	22.34	28.30
0.006	23.65	27.20	24.67	21.95	28.13
0.007	23.52	27.01	24.31	21.50	28.04
0.008	23.41	26.87	24.05	21.19	27.98
0.009	23.30	26.72	23.75	20.78	27.93
0.01	23.20	26.56	23.56	20.50	27.83
0.02	22.20	25.36	21.83	18.05	27.18

Table 3. Mixed Noise at Zero Mean and Different Variances and SSIM of Different Filters and Special Filter

Noise Variance	SIMM				
	Wavelet denoising	*Median filter*	*Wiener filter*	*Bilateral filter*	*Special filter*
0.001	0.82	0.77	0.78	0.52	0.88
0.002	0.82	0.75	0.76	0.49	0.88
0.003	0.82	0.73	0.74	0.46	0.87
0.004	0.82	0.72	0.72	0.44	0.87
0.005	0.81	0.71	0.71	0.41	0.87
0.006	0.81	0.69	0.69	0.39	0.87
0.007	0.81	0.68	0.68	0.37	0.87
0.008	0.81	0.67	0.66	0.35	0.87
0.009	0.81	0.66	0.65	0.33	0.87
0.01	0.81	0.65	0.63	0.31	0.86
0.02	0.80	0.57	0.53	0.19	0.85

Table 3. Mixed Noise at Zero Mean and Different Variances and SNR of Different Filters and Special Filter

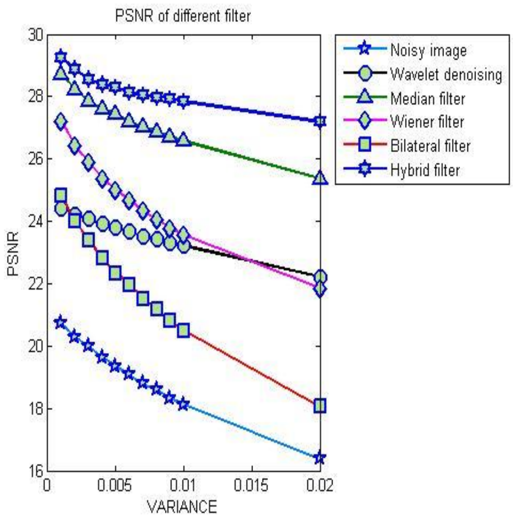
Noise Variance	SNR				
	Wavelet denoising	*Median filter*	*Wiener filter*	*Bilateral filter*	*Special filter*
0.001	22.47	26.77	25.26	22.86	27.30
0.002	22.28	26.28	24.46	22.04	26.92
0.003	22.12	25.91	23.94	21.45	26.60
0.004	21.96	25.65	23.42	20.86	26.42
0.005	21.85	25.49	23.04	20.40	26.36
0.006	21.71	25.26	22.73	20.01	26.18
0.007	21.58	25.07	22.37	19.56	26.10
0.008	21.47	24.92	22.11	19.24	26.04
0.009	21.36	24.78	21.81	18.84	25.99
0.01	21.26	24.62	21.62	18.55	25.89
0.02	20.26	23.42	19.89	16.11	25.24

Table 4. Mixed Noise at Zero Mean And Different Variances And MSE of Different Filters And Second Special Filter

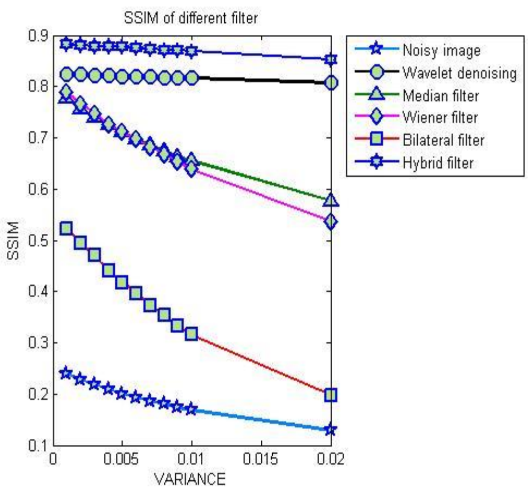
Noise Variance	MSE				
	Wavelet denoising	*Median filter*	*Wiener filter*	*Bilateral filter*	*Special filter*
0.001	5.96e+5	5.04e+5	5.31e+5	5.85e+5	4.96e+5
0.002	6.01e+5	5.13e+5	5.48e+5	6.08e+5	5.02e+5
0.003	6.06e+5	5.19e+5	5.59e+5	6.26e+5	5.07e+5
0.004	6.10e+5	5.24e+5	5.71e+5	6.45e+5	5.10e+5
0.005	6.14e+5	5.27e+5	5.78e+5	6.62e+5	5.11e+5
0.006	6.18e+5	5.31e+5	5.89e+5	6.77e+5	5.14e+5
0.007	6.22e+5	5.35e+5	5.99e+5	6.95e+5	5.16e+5
0.008	6.25e+5	5.38e+5	6.06e+5	7.09e+5	5.17e+5
0.009	6.29e+5	5.41e+5	6.15e+5	7.27e+5	5.18e+5
0.01	6.32e+5	5.45e+5	6.21e+5	7.41e+5	5.20e+5
0.02	6.67e+5	5.72e+5	6.81e+5	9.01e+5	5.32e+5

Table 5. Mixed Noise at Zero Mean and Different Variances And RMSE of Different Filters and Second Special Filter

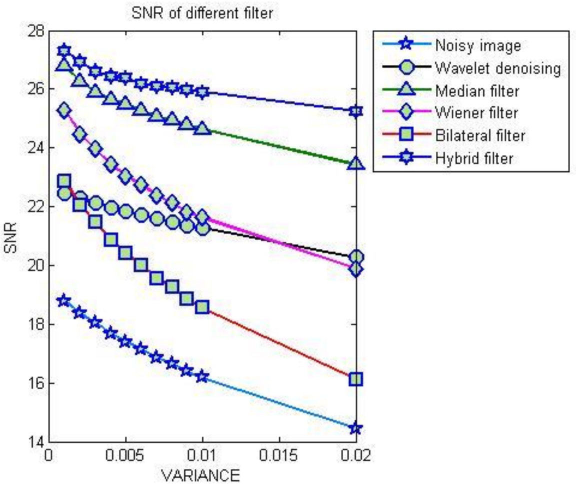
Noise Variance	RMSE				
	Wavelet denoising	*Median filter*	*Wiener filter*	*Bilateral filter*	*Special filter*
0.001	7.72e+2	7.10e+2	7.29e+2	7.65e+2	7.04e+2
0.002	7.75e+2	7.16e+2	7.40e+2	7.80e+2	7.08e+2
0.003	7.78e+2	7.20e+2	7.48e+2	7.91e+2	7.12e+2
0.004	7.81e+2	7.24e+2	7.56e+2	8.03e+2	7.14e+2
0.005	7.83e+2	7.26e+2	7.62e+2	8.13e+2	7.15e+2
0.006	7.86e+2	7.29e+2	7.67e+2	8.22e+2	7.17e+2
0.007	7.88e+2	7.31e+2	7.74e+2	8.33e+2	7.18e+2
0.008	7.91e+2	7.33e+2	7.78e+2	8.42e+2	7.19e+2
0.009	7.93e+2	7.36e+2	7.84e+2	8.52e+2	7.19e+2
0.01	7.95e+2	7.38e+2	7.88e+2	8.61e+2	7.21e+2
0.02	8.17e+2	7.56e+2	8.25e+2	9.49e+2	7.29e+2



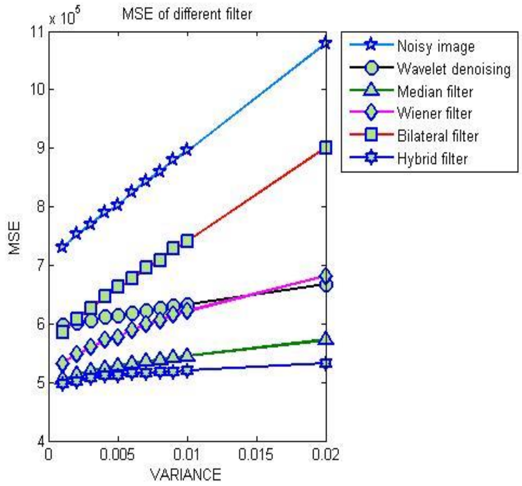
(a)



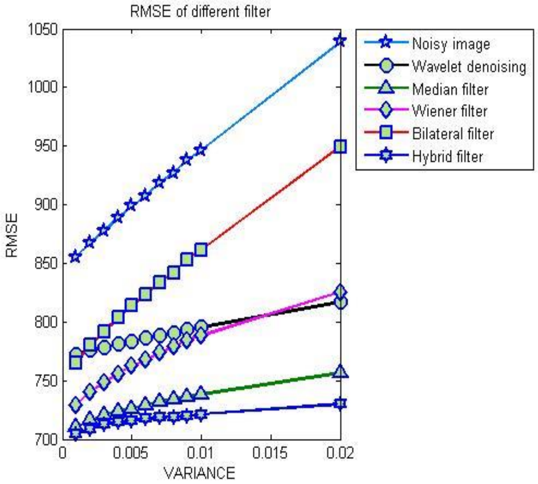
(b)



(c)



(d)



(e)

(a) Graph PSNR versus variance (b) Graph SSIM versus variance (c) Graph SNR versus variance (d) Graph MSE versus variance (e) Graph RMSE versus variance

Figure 12. represents the original white color image, mixed noise image and filtered images by different filters. Performance parameter calculates the performance of all the filters. PSNR, SNR, and SSIM should be high for a denoised image as compare to noisy image while RMSE and MSE should be low for a denoised image as compare to noisy image.

SNR, PSNR, SSIM of the original image decreases and MSE and RMSE of the original image increases as the mixed noise is added to the original image. This is shown in FIRST TABLE. SECOND TABLE shows that Special filter has highest PSNR than other filters at all variances. Median filter has PSNR near to Special filter while bilateral filter has lowest PSNR. THIRD TABLE shows that Special filter has highest SSIM. Wavelet filter has SSIM near to the Special filter while bilateral filter has lowest SSIM. FOURTH TABLE provides information that Special filter has highest SNR than other filters during all test cases. Bilateral filter has lowest SNR. FIFTH TABLE represents that Special filter has lowest MSE than other filters. Median filter has MSE close to the Special filter while bilateral filter has highest MSE. In TABLE 6 Special filter has lowest RMSE during all experiment cases. Bilateral filter has highest RMSE.

Graphs are plotted using data of the tables to show clear comparison among all filters. Pentagon marked blue line is used to indicates noisy image, circular marked black line represents DWT, triangular marked green line represents median filter, diamond marked pink line indicates wiener filter, square marked red line indicate bilateral filter and hexagon marked blue line represent the Special filter.

Graphs show that the Special filter has higher value of PSNR, SSIM, SNR and lower value of MSE, RMSE.

10. Conclusion

When the image is noised by gaussian noise then it is found after observing all results that Median filter's performance is better than wiener filter but it has lower SSIM than wiener filter and Wiener filter produce better results among all filters. When the image is noised by speckle noise then it is found after observing all results that bilateral filter's performance is better among all filters. It has highest PSNR, SSIM, SNR and lowest MSE, RMSE. When the image is noised by Salt and pepper noise then it is found after observing all results that Median filter's performance is better than all filters. It has highest SNR, SSIM, SNR and MSE, RMSE. When the image is noised by mixed noise then it is found after observing all results that:

a) Median filter's performance is better than discrete wavelet transform (DWT) denoising technique, wiener filter and bilateral filter because it has higher PSNR, SNR and lower MSE, RMSE.

b) Special filter's performance is better than discrete wavelet transform (DWT) denoising technique and different filters like median filter, wiener filter and bilateral filter. It has highest PSNR, SSIM, SNR and lowest MSE, RMSE.

Special filter provides images clear and visually better quality. Special filter is able to recover much more detail of the original image and provides a successful way of image denoising and there is almost no detectable deterioration in the image quality.

11. FutureWork

Mixed noise can be made more complex by adding more different types of noises. More performance parameters can be calculated to study behavior of Special filters. A better Special filter model can be designed using convolution based filter, diffusion filter *etc*. If Special filter will be implemented with EMD method, more denoised image can be achieved. If two dimensional data of a noisy image is converted into one dimensional data then more denoised image can be obtained by applying different denoising filters or denoising techniques on the one dimensional data. A better Special filter can be implemented using DWT denoising technique with other types of filter.

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